CHANGE DETECTION FOR EARTHQUAKE DAMAGE ASSESSMENT IN BUILT-UP AREAS USING VERY HIGH RESOLUTION OPTICAL AND SAR IMAGERY

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1. INTRODUCTION

Information on the impact of natural disasters (e.g. earthquakes) can be derived from suitable satellite imagery by comparing data from a chosen reference before the event (pre-event) to imagery acquired shortly after the event (post-event). Optical very high spatial resolution (VHR) sensors (e.g. QuickBird) have spatial resolutions smaller than 1 m. Some of these sensors have existed for almost a decade and have already imaged large parts of the Earth. The increased availability of this type of sensor and their growing image archives that are frequently updated, make VHR optical data well suited as the pre-event reference data source.

The advantage of synthetic aperture radar (SAR) imagery is its relative insensitivity to atmospheric conditions and independence from sun illumination. Thus, SAR data availability shortly after an event is in principle only based on the SAR sensor's orbiting characteristics, i.e. the sensor's revisit capability. Spaceborne VHR SAR only became available recently, when the new COSMO-SkyMed and TerraSAR-X sensors were launched in 2007. Both sensors have spatial resolutions down to 1 m. A major improvement over coarser spatial resolution legacy spaceborne SAR sensors, such as Envisat or Radarsat-1, is that VHR SAR can be used to analyze the structural integrity of individual urban structures, such as buildings and infrastructure elements. However, the spaceborne VHR SAR data archives are relatively recent and have limited pre-event imagery. Consequently, VHR SAR is not yet a reliable source for pre-event reference data.

In this paper, which generalizes and extends the work presented in [1], we propose a novel method to assess the structural status (i.e. damaged or undamaged) of individual, rectangular buildings affected by a catastrophic event using pre-event VHR optical and post-event detected VHR SAR imagery. First, the 3D measurements of a building are estimated from the pre-event imagery. The building measurements and the acquisition parameters of the post-event VHR SAR scene are used to predict the expected SAR signature of the building in the post-event SAR scene using a SAR simulator. Then, the similarity between the predicted SAR data and the actual SAR data is computed. High similarity values suggest no change and that a building is likely to be intact, while small similarity values

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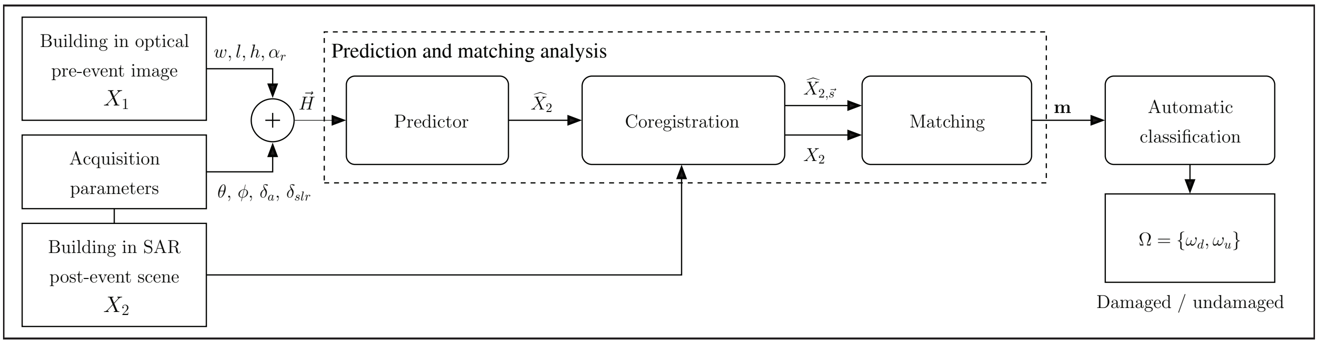

Fig. 1. Block scheme of the proposed method.

suggest the opposite. The similarity decision is based on a Bayesian classifier which is applied in the final step of the procedure. The classifier can be trained either in a supervised or in an unsupervised way using the Expectation Maximization (EM) algorithm.

2. PROPOSED METHODOLOGY

Let us consider the subset of a pre-event VHR optical image X_1 showing a building and the corresponding subset of a post-event VHR SAR scene X_2. Let $\Omega = \{\omega_u, \omega_d\}$ be the set of classes of undamaged and damaged buildings, respectively. Damaged buildings in VHR SAR do not have an unique pattern with which they can be easily detected [1]. Therefore, we model the problem of classifying a building into the classes ω_u and ω_d by evaluating in X_2 the presence or absence of the expected VHR SAR signature of the undamaged building. To do this, we extract the parameters of a building from the pre-event imagery, predict its VHR SAR signature in the post-event SAR scene (assuming that the building is undamaged), and compare the simulation with the actual scene. Similarity between simulation and actual scene indicates that a building is likely to be intact, whereas dissimilarity indicates the opposite. As shown in Fig. 1, the proposed approach consists of 3 main sections: 1) Extraction of parameters; 2) Prediction and matching analysis (PMA) which results in the match value m; and 3) Supervised or unsupervised classification of m into ω_u or ω_d.

2.1. Building parameter extraction

The building width w, length l, height h, and the pitch of the roof α are estimated from X_1. From the post-event VHR SAR data we extract the azimuth resolution δ_a, the slant range resolution δ_{slr}, the incidence angle θ and the aspect angle ϕ with which the building was imaged by the SAR sensor. Thus, a simulation is parameterized in the following manner $\vec{H} \equiv \{w, l, h, \alpha, \theta, \phi, \delta_a, \delta_{slr}\}$.

2.2. Prediction and matching analysis

A radar imaging simulator is used to convert $\vec{H}$ to $\widehat{X}_2$, i.e. the undamaged building SAR signature. For the evaluation of the match between $\widehat{X}_2$ and X_2, the two images are coregistered:

$$m = \max_{\vec{s}} \left\{ F[\widehat{X}_{2,\vec{s}}(\vec{H}), X_2] \right\}, \tag{1}$$

with F being the similarity measure and $\widehat{X}_{2,\vec{s}}$ the translation of the image $\widehat{X}_2$ by the two dimensional vector $\vec{s} = \{\Delta x, \Delta y\}$. The result of this maximization is also the final result of the evaluation of the matching between the simulated and the actual scene.

For F we use the normalized mutual information (NMI) [2]:

$$NMI(\widehat{X}_2, X_2) = \frac{H(\widehat{X}_2) + H(X_2) - H(\widehat{X}_2, X_2)}{\frac{1}{2}[H(\widehat{X}_2) + H(X_2)]}, \tag{2}$$

where $H(\widehat{X}_2)$ and $H(X_2)$ are the entropies of $\widehat{X}_2$ and X_2, respectively, and $H(\widehat{X}_2, X_2)$ is their joint entropy.

2.3. Identifying damaged and undamaged buildings

After the PMA, we classify the building into $\Omega = \{\omega_u, \omega_d\}$. Assuming that both class distributions are Gaussian, we perform this using Bayes rule:

$$\text{Decide } \omega_u \text{ if } p(Y(i)|\omega_u) \cdot P(\omega_u) > p(Y(i)|\omega_d) \cdot P(\omega_d);\ \text{otherwise decide } \omega_d, \tag{3}$$

where $P(\omega_u)$ and $P(\omega_d)$ are the prior probabilities of the classes ω_u and ω_d, respectively. The conditional probability density functions are denoted by $p(Y|\omega_u)$ and $p(Y|\omega_d)$, whereas Y is the random variable representing the m values of the I observations in the set $Y_{PMA} = \{Y(i), 1 \leq i \leq I\}$.

In case a training set is available, the parameters for (3) are calculated in a supervised way. However, in reality, it is often difficult to define a suitable training set. In these situations we propose to derive the statistical parameters and the prior probabilities of the two classes in an unsupervised way using the EM algorithm [3].

3. EXPERIMENTAL RESULTS

We demonstrate the feasibility and analyze the performance of the proposed method on a subset of Yingxiu, Wenchuan County, China, which was heavily damaged in the Sichuan earthquake on May 12, 2008. For the experiments, we use QuickBird pre-event optical data, and TerraSAR-X and COSMO-SkyMed post-event SAR data. Post-event QuickBird and WorldView-1 imagery as well as ground photography is used as reference data for the validation of the results. The analysis is based on a set of 30 buildings of various sizes and heights.

For the supervised classification of the 30 test buildings we perform the training with the post-TSX data and the testing with the post-CSK data and vice versa, thus testing the robustness and the generalization capabilities of the proposed approach. Note that we had to exclude three buildings from the analysis in the post-TSX data as they were located in the shadow area of a mountain. Table 1 provides the confusion matrices from the two supervised classifiers. The omission errors for ω_d are very small, and can be interpreted as almost all damaged buildings are detected correctly. Their respective commission errors range between 7.7% - 13.3% indicating that the method tends to moderately overestimate the damage. The overall mean accuracy of 91.2% shows that the proposed method is well suited for damage assessment using VHR optical pre-event and VHR SAR post-event data.

The confusion matrices of the unsupervised classifiers are listed in Table 2. The classification results of the buildings in the post-CSK scene (right columns of table) show that class ω_d has no omission errors, and only slightly

Table 1. Confusion matrices for the supervised classifiers.

		post-TSX		post-CSK	
		True class		True class	
		ω_d	ω_u	ω_d	ω_u
Estimated class	ω_d	15	2	12	2
	ω_u	0	13	1	12
Omissions		0.0%	13.3%	7.7%	14.3%
Commissions		13.3%	0.0%	15.4%	7.1%
Accuracy		93.4%		88.9%	

Table 2. Confusion matrices for the unsupervised classifiers.

		post-TSX		post-CSK	
		True class		True class	
		ω_d	ω_u	ω_d	ω_u
Estimated class	ω_d	14	7	15	3
	ω_u	0	6	0	12
Omissions		0.0%	53.8%	0.0%	20.0%
Commissions		50.0%	0.0%	20.0%	0.0%
Accuracy		74.1%		90.0%	

higher commission errors compared to the supervised classification. Instead, the results from the post-TSX scene (left columns of table) show that many undamaged buildings are classified as ω_d, while there are no damaged buildings which are classified as ω_u.

4. CONCLUSION

The results show that the method is able to distinguish between damaged and undamaged buildings with an overall accuracy of about 90% and 80% using the supervised and unsupervised classification procedures, respectively. Overall, the method misclassifies more undamaged buildings as damaged buildings than vice versa providing an upper limit for building damage. This misclassification is related to buildings which are not isolated, i.e. they are affected by scattering from other objects in their immediate surrounding, which is not modeled in our approach. Greater details on the method and experimental results will be reported in the full paper.

5. REFERENCES

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